

Applications of Nonlinear Dynamics to Resiliency Analysis

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Abstract— Resiliency maybe defined as “the ability of an entity—e.g., asset, organization, community, region—to anticipate, resist, absorb, respond to, adapt to, and recover from a disturbance from either natural or manmade events.” The loss of resiliency of these entities often represents high consequence but low probability events whose statistics are often governed not by the Gaussian distributions. In this paper we will report on our recent and ongoing work in the development of quantitative tools to detect “hidden” emerging qualitative changes in communities’ evolution such as utilities/public infrastructures, environment, public health, and financial systems. A key tool of choice is non-linear dynamics (NLD). The development of nonlinear dynamics and its applications to complex physical/engineering systems have been ongoing for the last few decades. It emerges as a major mathematical physics discipline from the study of turbulence even though it has an even earlier signature in the work of Poincare on celestial mechanics. NLD focuses on the study of dynamical systems which are deterministic and yet has no long term predictability due to the highly nonlinear nature of the interactions governing their evolution. That unpredictability arises not just from noise which is inevitably present in real-world systems. The hallmark of such systems is that their temporal behavior often looks chaotic, noise-like, and random. The “true” nature of the state of the system may not be readily apparent. This problem becomes particularly acute when the system is in the process of transiting between stability and instability (or vice-versa). Timely forewarning of these transitions is at the heart of resiliency analysis. A judicious and knowledge-based analysis using the metrics offered by NLD may reveal systematics of the dynamical evolution of these resilient communities which are otherwise “hidden”. This approach would form the basis for a set of quantitative tools to detect “hidden” emerging qualitative changes in resilient community evolution and thus a forewarning capability of impending potential serious impacts. These analyses may be used off-line for knowledge base build-up for any one particular resilient community. But equally importantly they may be employed in real-time so that timely corrective action may be initiated.

We will use a range of metrics to compare the performance of the system to that of other systems and to its

own previous performance. The technique is applicable to any resilient systems whose temporal behavior may be quantitatively observed. For the present work we will focus on the electrical power grid. For example, Figure 1 shows 3 months of minute-by-minute Exelon electric power demand data measured at Argonne in 1999. At first glance, these data seem noisy and possibly even random. Figure 2 plots the number of apparent degrees of freedom of the system in the data on the vertical axis versus the number of available degrees of freedom on the horizontal axis. Pure random data use virtually all degrees of freedom, as shown by the blue points in Figure 2. The measured electric power data clearly saturate around 4.5 to 5.0 degrees of freedom, and are thus far from random. Furthermore, if the saturated degrees of freedom (4.5–5.0) change going forward, the change will indicate that system operations are experiencing otherwise potentially unnoticed perturbations.

NLD has many other constructs (or metrics) that are capable of measuring *quantitatively* the *qualitative* changes of the system dynamics that are critical in recognizing/detecting emerging or impending changes in system resiliency. Analysis using this array of metrics on our data will be presented and their significance discussed. Different metrics may have different sensitivities to different infrastructure system dynamics. The sensitivities and reliabilities of these metrics would be carefully calibrated. The calibration is done by using data generated available industry historical field data and models that has known transition between stable and unstable states. The calibrated metrics form the backbone of an integrated methodology to be used in evaluating infrastructure system resilience. If this methodology is integrated into the control/command facility of an electrical power system, real-time updates of these metrics may provide an early detection capability for emerging threats to system resiliency. The same methodology and philosophy maybe applied to other systems of interest. Implications of our work will be addressed.

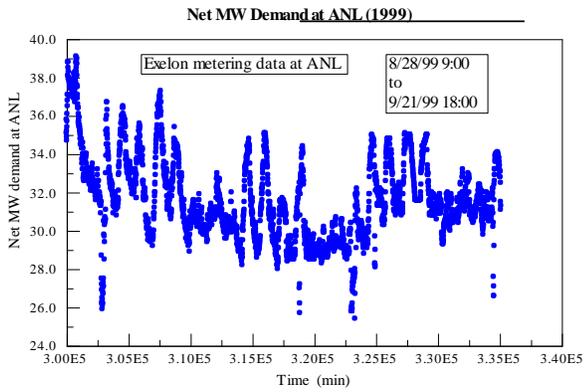


Fig 1. (Argonne) Electric Power Demand Data

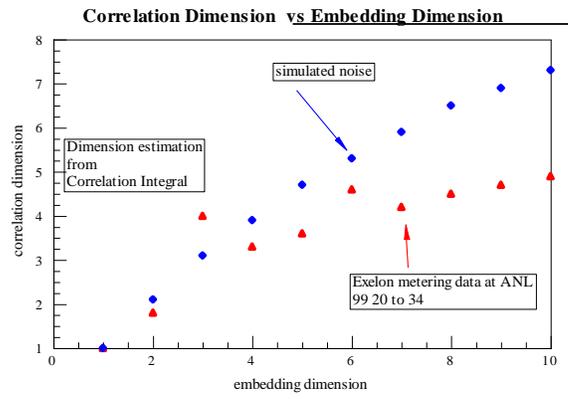


Fig. 2. Apparent (Red) and Available (Blue) Degrees of Freedom

Keywords—Non-linear dynamics, critical infrastructure, resiliency